MONITORING TRUCKS TO REVEAL BELGIAN GEOGRAPHICAL STRUCTURES AND DYNAMICS: FROM GPS TRACES TO SPATIAL INTERACTIONS

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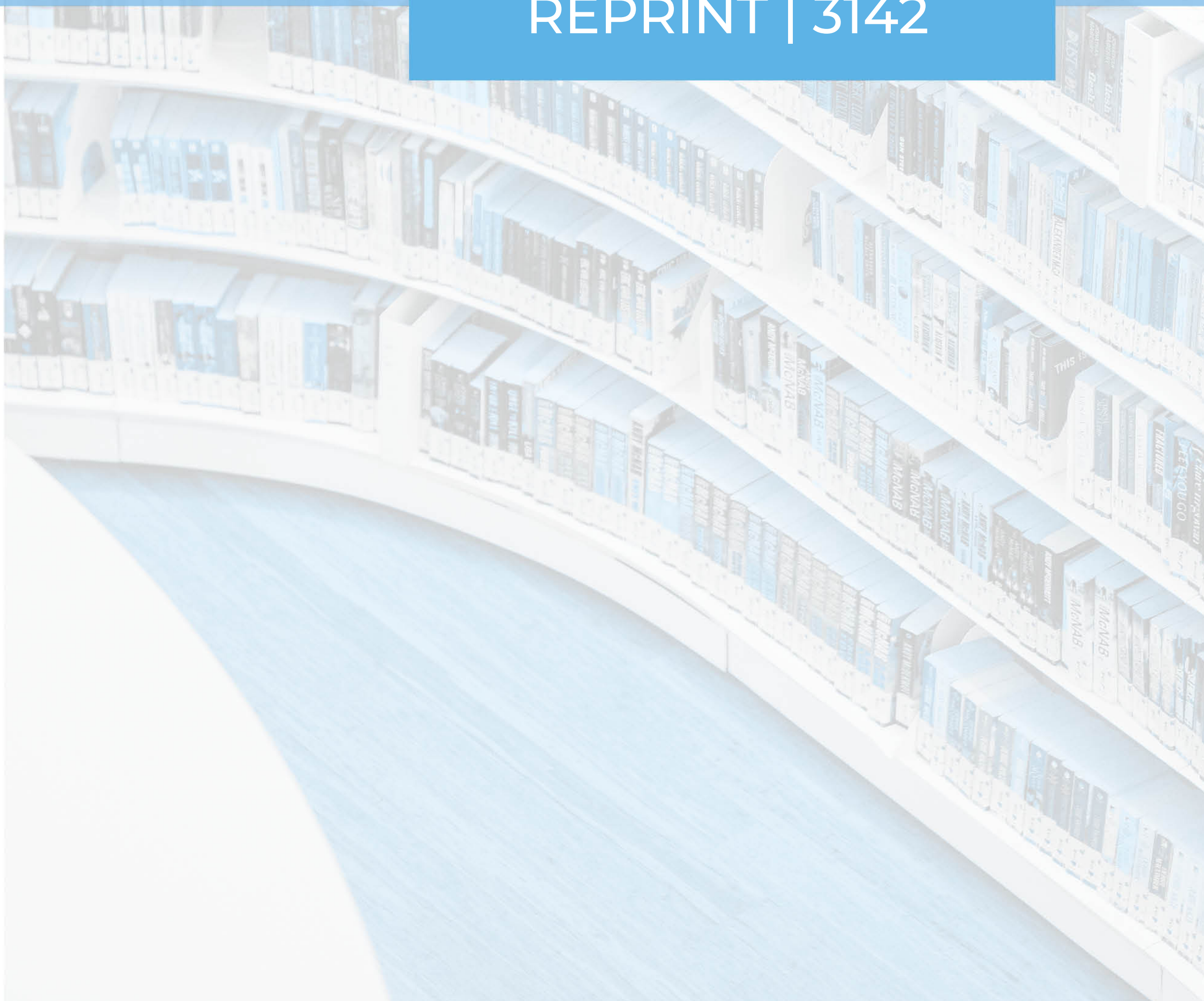

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Monitoring trucks to reveal Belgian geographical structures and dynamics: From GPS traces to spatial interactions

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ABSTRACT

Despite the fact that freight transport has a huge impact on the economy and the environment, Belgian datasets have always been scarce or restricted to very small a-spatial samples. Spatial data collected in Belgium for toll-paying trucks are here examined, and geographical structures and dynamics are extracted from this massive dataset. The originality of this dataset is its exhaustivity and its real-time approach: the location of all the trucks circulating in Belgium is collected every 30 s.

The paper first relates to the methodology applied when using and transforming big data generated by On Board Units GNSS (cleaning, transforming and pre-processing). Second, it maps and comments on the movements (traffic) and stops of trucks within the whole country, providing a clear picture of the Belgian situation, useful for regional planners and logistics companies. Finally, the flows of trucks observed between Belgian locations enable the country to be divided into mathematical communities of places that interact the most. Analyses are performed for sub-categories based on the country of registration, underlining the spatial specificities of freight transit in Belgium. This exploratory spatial data analysis enables to reveal not only multi-level spatial structures associated with urban hierarchies and the transport infrastructure, but also firm locations or political organizations and to consider the complexity and interconnectivity of any measure taken for a more sustainable future. With a clear methodological framework to cope with the data pre-processing, this paper opens the way to various potential applications linked with freight transportation in Belgium.

1. Introduction

Since the second half of the twentieth century, trade liberalization has resulted in a rise in the production and consumption of goods, and hence the increasing importance of the logistics sector (Rodrigue et al., 2006; Verhetsel et al., 2015). Nowadays, the size of the European logistics market is worth about €878 billion, with a high level of interaction between the 28 countries (European Commission, 2015). Around 44% of this market results from the various transportation modes (water, air and land transportation) developed to deliver goods from the place of production to the place of consumption (Rodrigue et al., 2006). More specifically, road transportation includes 75% of all European logistics companies (European Commission, 2015). Despite the recent announcement of new delivery modes such as drones and robots, the road transportation of goods has strong inertia to change, reinforced by strict national and European legislation (Bernardino et al., 2015).

Belgium is particularly affected by these developments due to many factors, in particular the production and consumption of goods and the increasing importance of the logistics sector. Although the country is small (30,528 km^2), Belgium is densely populated (11 million inhabitants) and its central position in Western Europe gives the country the stature of an important and well-connected European crossroads. The relative volumes of consumption per capita or that of GDP per capita are stronger in Belgium than in the Eurozone (Eurostat, 2018), and Belgium has long had one of the strongest market potentials in Europe (Clark et al., 1969; Head and Mayer, 2011). Nevertheless, Belgium is characterized by an important level of heterogeneity, in terms of regional economic development and structure, in terms of administrative organization, and even in terms of cultural and linguistic properties. The country is made up of three administrative regions separated by a linguistic border: the northern, Dutch-speaking part of the country (the Flemish Region); the southern, French-speaking part (the Walloon

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Region); and the Brussels-Capital Region (BCR) which is constitutionally bilingual. From either side of the linguistic border, each Region presents its own characteristics, density of companies, rate of urbanization, etc. (Adam et al., 2017; Goffette-Nagot et al., 2011; Helgers and Buyst, 2016; Persyn and Torfs, 2016; Trabelsi et al., 2019). These differences also affect the transportation network: although Belgium has well developed water, rail and road networks, these are denser in the Northern part of the country, due to a higher population density and topography (De Keersmaecker et al., 2003; Jones et al., 2016; van der Herten, 2001).

Although Belgium has well defined transportation network, statistics on the circulation of trucks have always suffered from a lack of exhaustive spatial data, often restricted to surveys based on rather small samples or local counting station samples. It leads to a lack of accurate knowledge of how trucks circulate and stop in Belgium. However, the increasing development of Information and Communication Technologies (ICT), now allows us to follow people or vehicles in real-time, to record their spatio-temporal traces (this recording is either made with or without the agreement of the user), offering new opportunities to integrate terrestrial or aerial sensors (Fan and Bifet, 2013; Kitchin, 2013; Li et al., 2008; Miller, 2017). The real-time tracking of trucks has indeed become standard in many contexts: some companies responsible for the transport of high value goods have equipped their fleets with GNSS sensors, whether required or not by insurance companies (Viljoen and Joubert, 2019). Finally, electronic tolling based on GPS sensors is being implemented in some geographical contexts, from very local ones such as specific bridges, tunnels or roads to national ones.

Since April 1st, 2016 Belgium has implemented a Kilometer Charge System (KCS). Each heavy goods vehicle with a gross combined weight of more than 3.5 tons (hereafter called trucks) circulating on any Belgian road has to be equipped with an On Board Unit (OBU) which collects the GNSS location of the truck every 30 s. As the use of an OBU is mandatory, data collected through the KCS (and made available for this study) hardly suffers from any lack of representativeness. This paper proposes to use the KCS database as a proxy for the circulation of trucks in Belgium. Gathering accurate information about the circulation of trucks between locations in Belgium is crucial for the development of a strong logistic environment. The objectives of this paper are, firstly, to provide an accurate description of the circulation of trucks in Belgium, as well as determining the locations where trucks stop. Secondly, these outcomes are necessary steps to evaluate the interaction between Belgian locations by considering the number of trucks circulating between different areas. This enables us to determine logistic basins, essential information for regional planning. In addition, these interactions are analyzed by considering the nationality of the truck: do foreign trucks make the same contribution as Belgian ones within the national freight system?

Using various standard techniques of spatial analysis and after an initial step of data cleaning and preparation (Section 2), this contribution focusses on the road freight transportation system in Belgium. Section 3 maps traffic and stops, and discusses the underlying geographical realities while Section 4 divides Belgium into mathematical communities of locations with a stronger interrelation, based on the country of registration of the trucks. Finally, there is a discussion about the pertinence of this newly developed dataset with the objective of a better understanding of the circulation of goods within Belgium. Throughout, particular attention is paid to the identification of the existing and new issues emerging, when analyzing individual spatio-temporal data which were not initially developed for a scientific purpose.

2. From unstructured GPS data to structured spatio-temporal information

2.1. Tracking trucks in space and time

Point-count stations are commonly used to estimate the traffic (i.e. the flow of trucks circulating) on the road network. Nevertheless, these stations only make it possible to measure precisely the traffic on road sections where they are located; a modeling step is necessary to estimate the traffic elsewhere. Moreover, these stations do not extract in a reliable way the places where trucks drive from and to. No further information is available either about the kind of vehicle or the goods transported. Similarly, building more precise data through surveys results in neglecting the exhaustiveness (or worse, the representativeness) of the phenomena due to temporal or financial constraints. Obviously, a sample of logistics companies must be taken, and the low response rate would inevitably lead to really small samples, making it difficult to extract generalities (see Lombard, 1999, in the case of road transportation in France). Relying on models and samples may be avoided by analyzing the digital traces made by vehicles.

Analyzing traces left by objects is not a novel approach in transport geography. A synthesis is presented in Antoniou et al., 2011: pedestrians, cyclists and taxis have already led to spatio-temporal analyses in different geographical contexts, mainly at an intra-urban scale (Laurila et al., 2012; Thomopoulos et al., 2015). Sensors are placed on the road (counting areas, surveillance cameras), or installed on board (transponders, tachographs, GPS trackers, smartphones, etc. - Gingerich et al., 2016; Thakur et al., 2015). Generally, these papers often answer questions related to the efficiency of the road network (Flaskou et al., 2015) within a specific geographical area for example in some American states or emerging countries such as China or South Africa (Joubert and Meintjes, 2015; Kuppam et al., 2014; Ma et al., 2011). Similarly, to counting point stations, the lack of exhaustiveness and representativeness, as well as the absence of a validation process, are major criticisms of studies using ICT data.

2.2. From GPS traces to trips and segments

2.2.1. Description of the initial dataset

The Kilometer Charge is calculated according to the number of kilometers travelled, modulated by the maximum weight that can be carried by the vehicle and its euro-emission class (see www.viapass.be for the details). Moreover, it varies from one Region to another, as road network management is a regional rather than federal competence (even if the tariffs remain similar between all entities). Beside the collection of the data required for the computation of the toll, the OBUs also send anonymized GNSS coordinates every 30 s to a centralized computer server while the truck is in motion. However, when the truck stops (whether the engine is running or not), the OBU detects that the vehicle is not in motion and no GPS pings are emitted. When the stop is over and the truck starts to drive again, the OBU detects a movement and GPS pings are emitted once more. So, two successive GPS pings could have a time difference of more than 30 s (corresponding to a period where the truck has not moved). Unfortunately, no information about characteristics of the OBU or the trucks is provided (sleeping mode of the OBU, GPS signal accuracy or the ignition of the engine of the truck). Regardless of whether the road is tolled, GPS pings are only collected while the truck is in motion, and the database thus contains the exact location of all the trucks in circulation in Belgium. For the sake of this study, one week of records was made available by Viapass. In contrast to the current situation where there are many OBU providers in the Belgian market, only two OBU providers were available at the time of our sample (our dataset consists in the OBU from the national service provider Satellic and, for the time frame considered, can be considered as nearly exhaustive).

Following the work of Finance et al., 2019 that evaluates the urban polarization of a particular Belgian city, we define as a sequence of pings (here called GPS traces), a spatio-temporal ordered list of pings registered for a given truck identified by its ID. Each GPS point emitted by an OBU contains the following items: the truck pseudonymized ID (under the 'privacy by design' approach, this ID is randomly modified each day by the OBU), the coordinates of the GPS point, the time when the GPS ping was registered, the instant velocity and instant direction of the truck (computed from the GNSS chip within the OBU), the country of registration of the truck, its euro-emission class (i.e. a pollution class reference in Europe), and finally the gross maximum weight of the vehicle. Once ordered by ID and by timestamp, we get as many sequences of pings as trucks circulating during the week multiplied by the number of days, as the ID is specific to a given day.

This one-week sample of data covers the period from Monday 14 November 2016 to Sunday 20 November 2016. It contains over 799,000 distinct IDs, which correspond to trucks registered in 63 different countries and emitting over 270 million GPS points recorded on all Belgian roads (around 177,000 km). For the sake of clarity, the following analyses preceded by general cleaning and transformation steps are limited to weekdays, as it seems that weekends are specific periods with probable distinctive patterns. Fig. 1a shows that a clear and stable pattern: from Monday to Friday, the number of GPS points emitted per hour follows the same trend. This has to be compared with Saturday and Sunday where only a small amount of GPS pings is emitted. Although the pattern is stable and clear during working days, Thursday shows a particularity: due to a snowy period in north and central Belgium in the morning, the number of GPS pings was drastically reduced. These wintry conditions made the Belgian road network grind to a halt. Another clear pattern is presented in Fig. 1b: from Monday to Friday, more than 60% of the GPS points are emitted by Belgian trucks, followed by Dutch, Polish and German ones (these figures are consistent with the long-term average reported by Viapass). Nevertheless, a distinct pattern can be observed during the weekend, justifying our decision to exclude the information collected on Saturday and Sunday. During the weekend, only 50% of the GPS points are emitted by Belgian trucks. In addition, the ranking of the most frequent countries of registration is modified: Polish trucks emit more pings than Dutch ones, and Lithuanian ones more than French ones. The closure or the reduction of many economic activities (manufacturing industries, deliveries to shopping centers, etc.) during the weekend reduces the need for short-distance journeys, possibly more likely carried out by local trucks. In contrast, foreign trucks (especially those registered in Eastern and Central Europe) probably cover greater distances to reach important logistic hubs spread around Europe (ports, airports, highly specialized manufacturing locations). National-scale effects such as the French legislation restricting truck driving at weekends may also explain the strong differences between weekdays and weekends.

2.2.2. *Identifying sequences of points constituting individual trips*

Since most of the research used sampling methods that are case-specific, it is difficult to obtain converging criteria, thresholds or filtering operations to obtain reliable and usable geographical information from a raw GPS data structure. The common step within many publications is the identification of 'trips' and the origin-destination segments. Shen and Stopher (2014) identify this step as the main challenge due to the numerous issues linked with the loss of GPS signals, or the amount of noise recorded in the database. Fig. 2 follows this idea: each GPS ping is first considered within the spatio-temporal sequence of points emitted by a given OBU (the GPS trace). Second, based on the identification of specific events (being in this case the stops made), each sequence of pings is split into a sequence of trips (a subsequence of pings emitted between two events) for which the distance is computed (the Euclidean distance between each pair of GPS points, leading to approximate the network distance travelled by trucks, and here called per se).

Splitting the sequence of GPS points into a sequence of trips calls for specific criteria (Shen and Stopher, 2014). Unfortunately, the literature does not agree on what to apply since applications are constrained by the database used. While Joubert and Axhausen, 2011 use information about whether the engine is running, work done by Cich et al., 2016 considers pings which are constantly emitted by the sensor. These are able to detect areas where trucks stop by considering the concentration of pings, and link these with surveys provided by the driver (as followed by Schönfelder et al. in 2002 as well). Other papers are using simple temporal criteria, but without any consensus: Li et al. (2008) and Xiao et al. (2016) both use 30 min to determine a stop, while Rasmussen et al. (2015) use 2 min. In addition, Hess et al. (2015) write that a stop ranges between 2 and 20 min. To avoid the use of a temporal criterion only, other approaches have been developed. Zanjani et al. (2015) simply combine velocity and distance, while Guidotti et al. (2015) consider a multiplication of parameters that are unfortunately impossible to apply under particular circumstances. Alvares et al. (2007) have decided to combine the raw GPS pings with Points Of Interests (POI). By combining the location of the POI with areas where a stop is made, they are able to define the nature of the stop. However, this method raises questions about the quality of the match between the raw data and the most suitable POI closely located. Finally, Gingerich et al., 2016 combine a temporal criterion with the spatial characteristic of the stop (proximity to firms) to detect 1) primary stops that occurred when a transfer of goods took place between the vehicle and the location, and 2) secondary stops that correspond to stops that fulfill other needs (fuel refilling, drivers breaks). This method has the benefit to combine two approaches (temporal criterion and spatial characteristics of the stop), but like Alvares et al. in 2007, the quality of the match between stops and spatial characteristics may be unclear when a given area has a large variety of

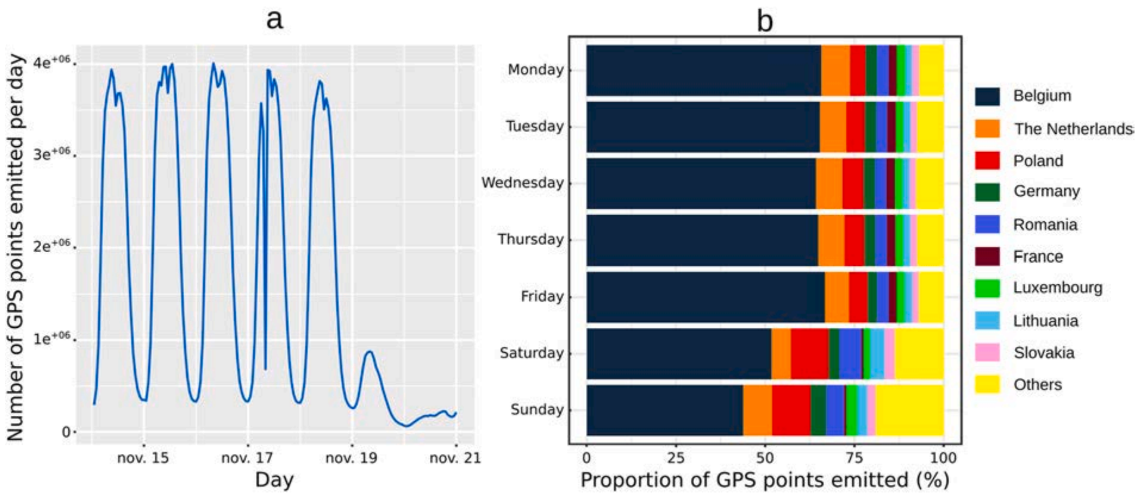

Fig. 1. Proportion of GPS pings emitted by: a) hour and b) country of registration of the trucks.

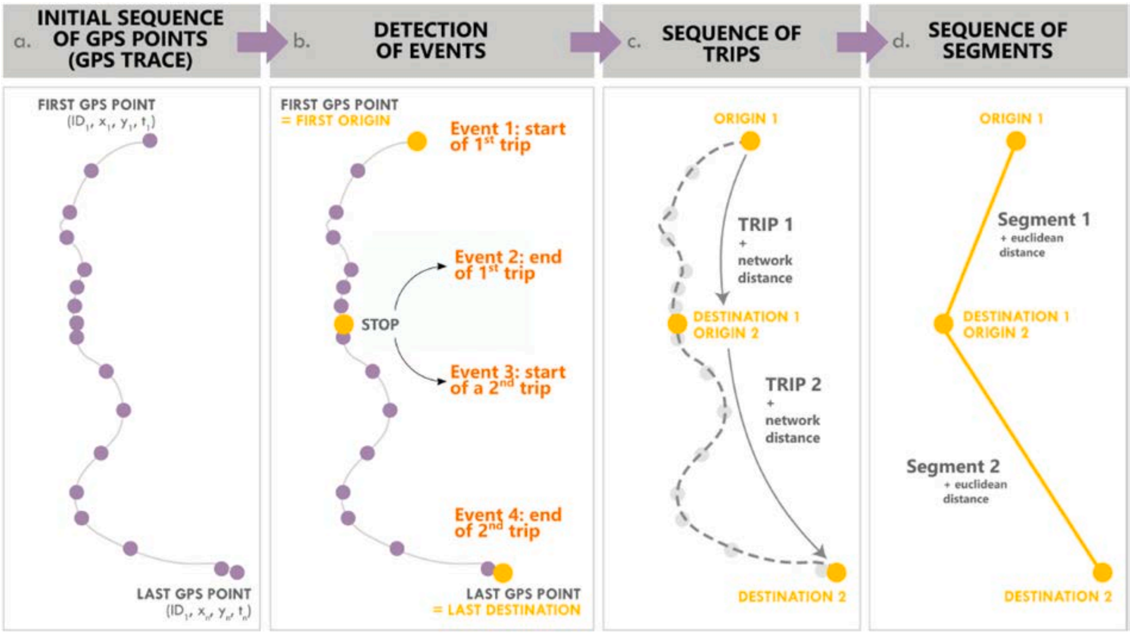

Fig. 2. Transformation of a GPS trace (a) into a sequence of trips (c) and a sequence of segments (d).

features (restaurant, gas station, industry, shops, or residence). It is important to make clear that most of these publications are mainly based on a specific type of vehicle, while the Viapass database used in this paper deals with all heavy goods vehicles with a gross combined weight of more than 3.5 tons. It therefore reflects a large variety of vehicles having different objectives (delivering industries, shops or private households), and then stopping in different areas (industrial areas, commercial units, residential places). Adding spatial characteristics in this paper may not bring useful insight due to the dense Belgian areas that are usually multi-functional.

Since the literature shows that there is no agreed way to detect stops based on a simple temporal criterion, it was decided to perform sensitivity analyses to detect the most suitable one that could be applied to all trucks. Analyses are applied for values of time ranging from 0 to 300 min. Fig. 3 illustrates the number of trips detected with the increase in the duration of the stops and shows that a threshold of 10 min corresponds to the beginning of the curvature of the slope, while a threshold of 20 min corresponds to the maximal value. With regard to the sensitivity analyses, it was decided that a stop corresponds to a delay of more than 10 min between two successive GPS pings.

This 10-minute threshold (consistent with the literature and discussed above) was chosen as it is sufficiently small to include the different reasons for of stops (loading, unloading, delivering, resting, etc.) without including small 'parasite' stops (congestion, traffic lights, small OBU distortion, etc.) and removing a large number of trips. It leads to the generation of two events (Fig. 2b), the end of the previous trip and later on, the start of the next one. Finally, the sequence of trips (Fig. 2c) is simplified into a sequence of segments (Fig. 2d), each of them connecting two geographical locations (OD pair) and two timestamps. This is made by putting aside the accurate spatio-temporal path followed by a truck during a trip and focusing only on the origin and the destination. Furthermore, the Euclidean distance has been computed for each segment (in addition to the network distance computed as mentioned above). It should be noted that filters have been applied to remove

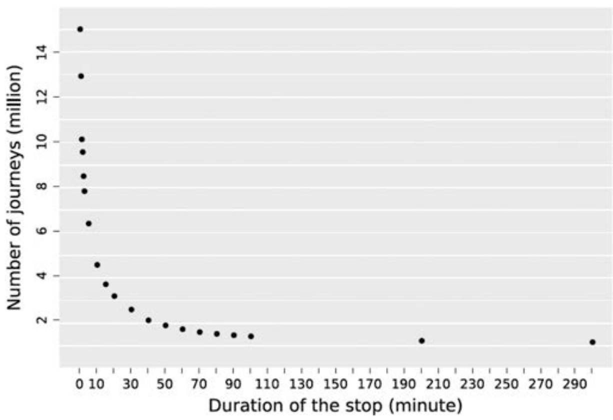

Fig. 3. Number of journeys detected for different duration of stops.

trucks that are moving solely over very small distances (e.g. moving without ever leaving a parking place) by ignoring sequences of less than 10 pings during a day (Please see Fig. A1, for detailed information).

Moreover, due to privacy protection, the ID identifying each OBU, and by extension a given truck, is randomized every night. This makes it impossible to follow a given truck during the five days of the sample, and suggests some precautions while detecting events in sequences of pings (especially with some of the very first or very last GPS points in a daily sequence). The renumbering is applied every day at an apparently random time between 01:50 am and 02:00 am, corresponding to the lowest traffic intensity. Hence, when a given ID (ID1) is randomized, it disappears in the database as a new one (ID2) (Fig. 4), leading to the creation of a spurious last destination for ID1 in a manner similar to the creation of a spurious first origin for ID2. To avoid considering fictitious events, and to avoid counting twice (under 2 distinct IDs) a given truck circulating on a given day (i.e. before and after 02:00 am), days have been redefined as independent periods of 24 h extending from initial day d 02:00 am to initial day d + 1 01:59 am. Fig. 4 shows how strong the potential effect could be of not redefining days by counting very first and very last appearances of each ID, i.e. events considered as first origin and last destination of sequences of pings. Once the new temporal design is applied, IDs appearing only after 01:50 am are excluded from the analysis (probably the trips of a renumbered truck), and the OD recorded between 01:50:00 am and 02:00:30 am are labeled as fuzzy and not considered as real origins and destinations per se (these are probably the last/first GPS point before/after the renumbering). Please see Fig. A1 for detailed information about this cleaning step.

2.2.3. Quality validation and corrections

After converting each GPS trace into a sequence of trips and segments, the consistency of these breakdowns is verified, as well as the attributes describing each segment. We show by three main cases what kind of corrections and suppressions have been made when inconsistencies are identified (Fig. 5 and Fig. A1, for detailed information). The detection of inconsistencies relies on the cross-comparison, for each pair of consecutive events, of information about time and location. These cases are made possible by the comparison of the Network distance and the Euclidean distance computed between each Origin and Destination, as well as the timestamp and the velocity observed between couples of GPS pings and between couples of ODs.

The first case (Fig. 5a) considers the initial sequence of GPS points, detects one-off glitches in the sequence and, if so, rectifies the spatio-temporal information (Cich et al., 2016). Let us consider two consecutive pairs of pings (i.e. three pings): the intermediate point is suppressed and distances are recomputed if two consecutive short temporal gaps of 30 s are associated with two significantly large distances (an arbitrary threshold has been fixed at three kilometers to avoid considering a tunnel effect: the longest tunnel in Belgium is the Leopold 2 tunnel which is located in Brussels and is 2534 m long). This intermediate point is an error resulting from many potential causes, e.g. bad reception of the GPS signal or incorrect transmission of the information by the OBU. Nevertheless, if this error is recurrently observed in a given sequence of pings, the totality of the trace is excluded from the analysis as this could be two OBUs using the same ID (by extension two distinct trucks having the same identifier). As explained in a previous Section, the daily renumbering of the ID is done by the OBU itself without considering the possibility that this new ID is already being used by another OBU.

In the second case (Fig. 5b), the spatial continuity in a sequence of segments is verified and corrected. When there is a small Euclidean distance (arbitrary threshold fixed at three kilometers – see tunnel effect above) between a detected destination and the following origin (two successive events), we assess whether these two events are located in the same basic spatial units (BSU) (cells of 1 km^2 - grid presented in Section 3). On the one hand, when the spatial gap is so small that the events are found in the same BSU, no correction is applied. On the other hand, if they are attributed to two different BSUs, we attribute these events to one of the two BSUs. The one selected is chosen based on the instant velocities measured by the OBU at the destination and at the following origin, considering that the most accurate location is characterized by a velocity equal to 0. This error is mainly due to the slow wake-up of the OBU after going into sleep mode for more than 15 min. The correction is applied as many times as the inconsistency is observed.

Finally, the third case applies to large spatial discontinuities between a destination and the following origin when a stop occurs (Fig. 5c). In that case, there is an effective loss of information in tracking the vehicle, as it is impossible for a truck to start a trip in a separate location from where it ended the previous journey (trucks leaving and then entering again in the country are not considered here in this third case). Whenever the distance between the destination and the following origin is consequent (more than an arbitrary threshold fixed here at three km) although a stop is detected (more than 10- min gap between a destination and the next origin), the reliability of the detected events is questionable. Indeed, this situation does not correspond to a stop but reveals an issue within the trace due to a possible loss of the GPS signal by the OBU, an error during the uploading of the data, an internal error of the OBU or a (voluntary) breakdown of the collecting system. To avoid excessive loss of information, it was considered acceptable that this case is observed only once for a given ID, with a specific correction. The two events detected as a destination and an origin are more likely the loss and the recovery of the GPS signal or the shutdown and the restart of the tracking unit. In this case, a correction is applied by merging the two segments detected before and after the doubtful stop into one sole OD segment linking the origin of the first segment and the destination of the second segment. If it appears several times, it is clearly impossible to rely on the veracity of the stops detected, and the GPS trace is deleted from the dataset. At the end of this automatic cleaning process, we end up

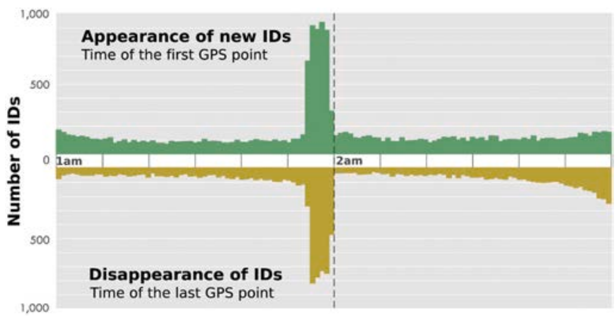

Fig. 4. Appearance and disappearance of the trucks' ID around 02:00.

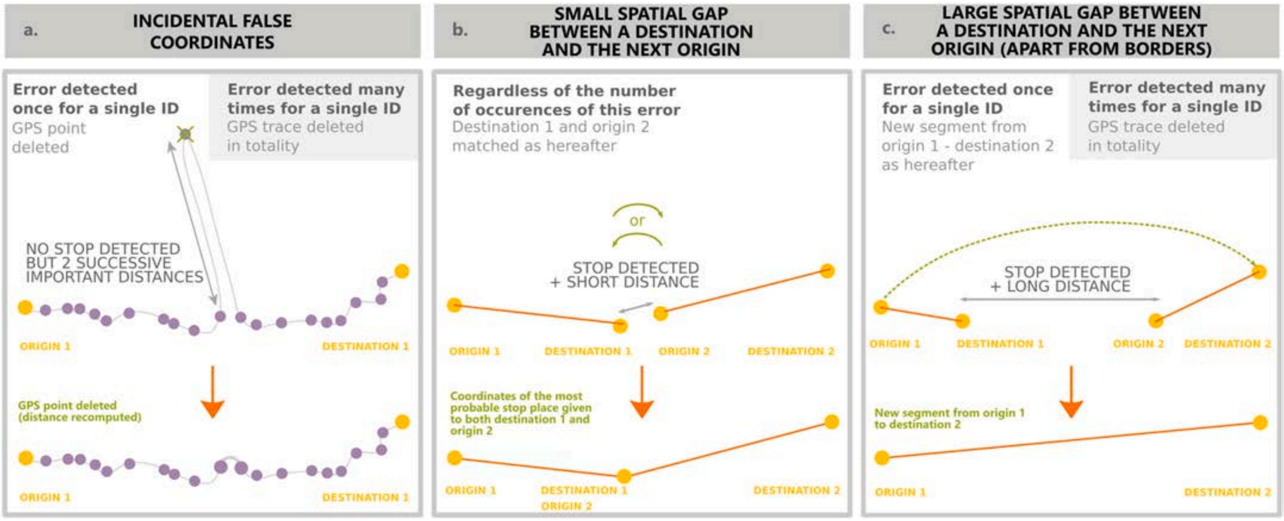

Fig. 5. Detection and correction of inconsistencies, according to the occurrence of errors observed for each ID.

with the deletion from the initial database of 11% of the GPS points and 21% of the truck's IDs (Table 1).

3. Mapping movements of trucks

Sustainable regional planning calls for a better knowledge of the various externalities linked with the transport of goods (Macharis and Melo, 2011; Rodrigue et al., 2006), and then requires better estimation of the circulation of trucks at the country level. This section aims to explore the circulation of trucks in Belgium (Section 3.1), as well as the geography of the places where they stop (Section 3.2). To do this, the entire country is divided into a grid of 1 km^2 squared cells (approximately 32,000). To avoid any discussion about the construction of this grid, we used the grid developed by Eurostat (2016).

3.1. Where do trucks circulate?

The number of different truck IDs in movement within each cell is calculated hour per hour, and further summed up for daily information. This method appears to be more consistent than just mapping the number of GPS points recorded in each cell: trucks trapped in a congestion zone (and driving slowly) would, in that case, emit many pings in a given cell, causing the traffic in congestion zones to be widely overestimated. In addition, this would also solve issues linked with the specificity of the roads (for instance, the curvature that reduces the velocity of the truck and hence leads to the emission of more GPS points than trucks driving in straight line). This leads to the computation of two indicators at the level of the cells: daily traffic (sum of the 24 hourly measures) and average daily traffic (daily traffic averaged over the five working days). Working at the level of a grid differs from the work done by Laranjeiro et al., 2019, but it allows a consistent overview of the Belgian situation instead of being concentrated on a small study area. The average daily traffic (Fig. 6a), clearly reveals the strong hierarchy of the road network, with high intensities of traffic around the largest cities and on the motorways. The peripheral roads of Brussels and Antwerp can be particularly well distinguished. Motorways linking the major economic clusters and neighboring countries are the places where traffic is the most dense. Here appears one of the indirect advantages of the Viapass System: the possibility of an accurate measure of the density of traffic for each point of the territory in real time. By using Viapass data, we get data in real time on all roads located in Belgium (no counting point stations, no sampling etc.). However, readers have to keep in mind that, although the dataset provided by Viapass is almost exhaustive, this study applies several cleaning procedures that could affect the outcomes.

3.2. Where do trucks stop?

Beyond the visualization of the places (cells of the grid) where trucks are passing, we now aim at detecting connections, that is to say the sum of the number of events 'origins' and 'destinations' per cell. Similarly to the traffic, connections are initially constructed hour by hour, cumulated over the entire day and averaged over the week (five working days), leading to a daily averaged number of connections (Fig. 6b). As expected, stops are mostly found in major urban areas, ports, airports and industrial sites. Economic activities are clearly shown once again as significant. High intensities of connections are found: firstly, at ports around the cities of Antwerp, Ghent and Zeebrugge; secondly along the Antwerp-Hasselt industrial axis (along the Albert Canal and the E313 motorway); and thirdly, in Liège-Namur-Charleroi (along the former Walloon 'Sillon industriel' and the E42) or around Brussels and, more especially, within the South-West - North-East axis (Macharis and Melo, 2011).

Table 1
Statistics related to the main cleaning cases.

	Truck IDs		GPS pings		OD segments	
	#	%	#	%	#	%
Initial database	798,435	100.0	269,194,440	100,0		
Erasing truck IDs with fewer than 10 GPS pings	719,425	90.1	265,564,849	98.6		
After temporal reconstruction (Box 2)	655,701	82.1	253,684,428	94.2	3,746,263	100.0
Final dataset after cleaning errors presented in Fig. 5	628,769	78.7	238,927,089	88.8	2,758,940	73.6

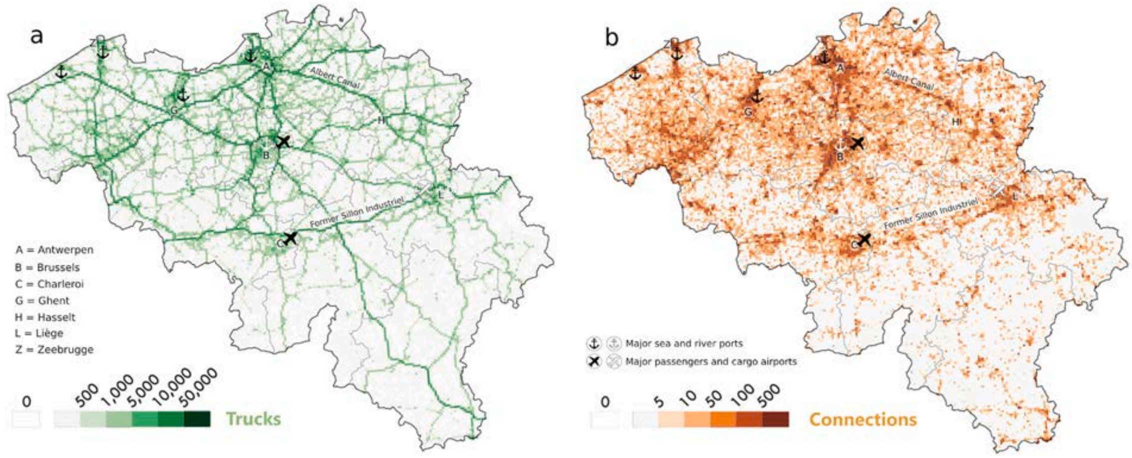

Fig. 6. Trucks in Belgium: average daily a) traffic and b) connections.

4. The national and international circulation of trucks

4.1. Different networks to demonstrate different realities

Due to the free circulation of people and goods in Europe, it is hard to know whether a truck is domestic or not. European Union cabotage regulations permits any truck registered in a European country to deliver goods in Belgium. Cabotage is 'the transport of goods or passengers between two places in the same country by a transport operator from another country' (European Union, 1993). The European Union regulates the cabotage as follows: 'a non-resident carrier is allowed pick up and deliver a further load inside the host country before returning to the border'. Due to the lack of accurate data, there are few results about cabotage for Belgium. The objective of this section is not to assess a possible effect of cabotage but to explore what the spatial differences are between trucks registered in Belgium and abroad, leading to preliminary results useful for future research on cabotage in Belgium. To do this, the 'domesticity' of each truck is evaluated based on two criteria: 1) the country of registration and 2) the location of the GPS points. First, each truck ID is associated with the country of registration of the vehicle and two categories are formed: *Belgian* and *foreign* trucks. Second, the location of each GPS point is considered to extract the 'domesticity' dimension of each truck circulating in Belgium. Two categories of trucks are defined here: 1) for a given truck, if all the GPS pings are emitted in Belgium, this truck is listed as circulating exclusively in Belgium (noted *intra* truck) and 2) in contrast, if at least one GPS point is located out of Belgian territory, this truck is listed as an international truck (noted as an *inter* truck). In that respect, a Belgian truck (according to the country of registration) crossing the border at least once will be considered as an *inter* truck. To sum up, four categories are created: 1) *Belgian,* 2) *foreign* trucks based on the country of registration, 3) *intra* and 4) *inter* measured by the location of GPS pings. 92% of the trucks registered in Belgium are *intra* trucks, while only 18% of the *inter* trucks are registered in Belgium. Within these Belgian *inter* trucks, 11% have their first origin and final destination within Belgium.

Fig. 7 presents the daily variation in the number of trucks in circulation and the number of GPS pings emitted, for the four categories of trucks. These two hourly variations follow an identical pattern: a high percentage of the total trucks/GPS points between 4 am and 6 pm, with a reduction starting around 2 pm. The four categories accurately follow

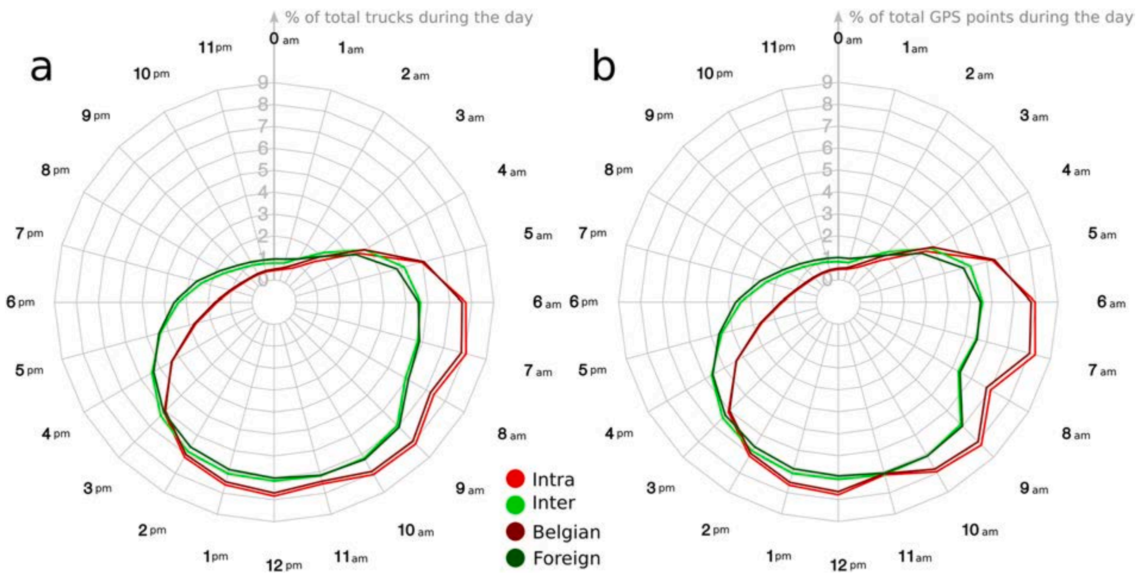

Fig. 7. Daily variation of a) trucks per hour and b) GPS points emitted per hour, for the four predefined categories of trucks.

two main tendencies: *intra* trucks and *Belgian* trucks have a similar shape, although *inter* trucks have a similar curve as the *foreign* trucks.

4.2. Determining interaction between places

The objective of this section is to evaluate how the interactions (pair of Origin and Destination, hereafter called OD pair) between places are organized in Belgium. Only GPS points that correspond to an Origin or a Destination are here considered and these two types of events are aggregated into the cell level (the grid was presented in Section 3). Interactions are then observed and analyzed between pairs of cells. For the sake of clarity and since *Belgian* and *foreign* trucks are respectively similar to *intra* and *inter* ones (Fig. 7), analyses are only applied on the *two first categories*. Fig. 8 maps OD segments between Belgian locations. For the sake of readability, two choices have been made: first, the origin and destination of these segments are aggregated into municipalities instead of the cell level and, second, only flows representing more than 100 and 250 segments are respectively considered for *Belgian* (Fig. 8a) and *foreign* trucks (Fig. 8b).

The results show different spatial organization. On the one hand, movements made by *Belgian* trucks (Fig. 8a) are centered on major cities and logistics/industrial areas. The port of Antwerp appears to be a major central area for truck movements, followed by the port of Ghent. The regional and provincial organization of the OD segments is quite clear. The linguistic border is a strong impediment to movement, with the exception of the area around Brussels. Secondary centers dominated by logistical locations and economic activities emerge: the West and East of the country. Their influences are mainly spreading to their neighbors' municipalities (interaction is reduced as the distance increases - Tobler, 1970). In contrast, foreign trucks (Fig. 8b) show that flows are mainly found between pairs of municipalities located close to the border. Entry and leaving points in Belgium are clearly identified. It demonstrates that most foreign trucks pass through Belgium without making any deliveries.

However, to refine this first exploratory analysis of how interaction is spatially organized, and to suggest a more concise finding, a community detection method is applied to the OD segments. Detecting groups of nodes that are tightly connected (called mathematical communities) has become quite popular in the analysis of large datasets and in complex network analyses (Newman and Girvan, 2004). Partitions maximize the density of intra-group connections with respect to the density of inter-group connections. Most of the methods are based on the maximization of the modularity, which has become a common way to quantify the quality of the partitions (Newman and Girvan, 2004). Modularity searches for a compromise between the minimization of the connections between nodes already classified in communities (*cut*) and the maximization of the number of communities found in the network (*diversity*). The higher the modularity, the better the partitioning into communities is correctly determined (Delvenne et al., 2010). The Louvain Method (Blondel et al., 2008) is here used to optimally maximize the modularity (Adam et al., 2018; Lambiotte et al., 2008). This heuristic was chosen because the Louvain Method is largely documented and is applied in several thematic areas, including commuting movements (Adam et al., 2018; Shen and Batty, 2018), communication networks (Erickson, 2010; Thomas et al., 2017) or transportation networks (Finance et al., 2019; Huang et al., 2018). This heuristic method maximizes modularity in two successive and iterative stages. First, the method groups into communities the nodes with an intense relation and which maximize modularity. Second, nodes that are classified in each community are merged into supra-nodes (these therefore represent communities formed in the first stage). Then, the Louvain Method begins the first stage again and seeks to group the supra-nodes, maximizing modularity before moving on to the second stage again. The first and second stages are therefore applied successively until the Louvain Method has approximated a maximum modularity. It is important to make clear that the Louvain Method implies that every cell linked with another one is classified, even those with very low levels of interactions, hiding the very diverse intensity of connection of places to the network. Therefore, it was decided to prune the networks by excluding meshes visited less than 10 times during the five days, to avoid giving too much importance to places connected very sporadically. The spatial extent of the communities resulting from the Louvain Method are shown in Fig. 9. The results are illustrated in the form of maps with an arbitrary choice of colors that represent the different communities. Each cell is then colored according to its community. We recall that a community consists in a group of places (cells) that are tightly interrelated. In that case, movements between pairs of OD are proportionally mainly found inside a single community rather than between two.

Fig. 9a presents the communities detected in the general OD network before removing cells visited less than 10 times, and considering the nationality of the truck. The spatial organization of communities detected in the *Belgian* network (Fig. 9b) is made of groups of contiguous places that are highly interconnected and hence characterized by strong interaction exchanges. These large groups correspond to the area of influence of the main economic hubs and logistics centers, fitting well with the urban hierarchy (Vanderstraeten and Van Hecke, 2019). The linguistic border is quite well delineated, with the exception of places located around Brussels. The BCR administrative limits are no longer

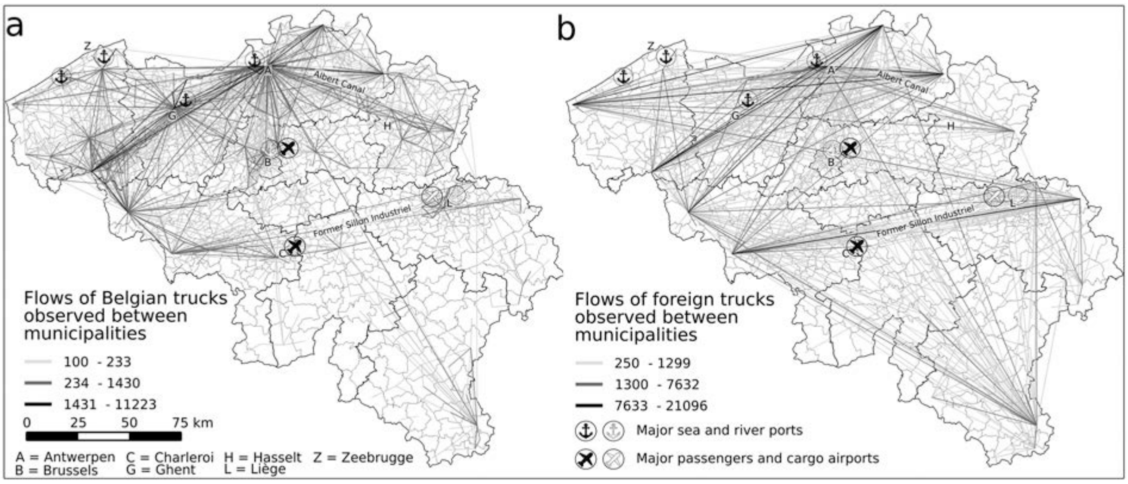

Fig. 8. Flows observed between municipalities for a) Belgian and b) foreign trucks.

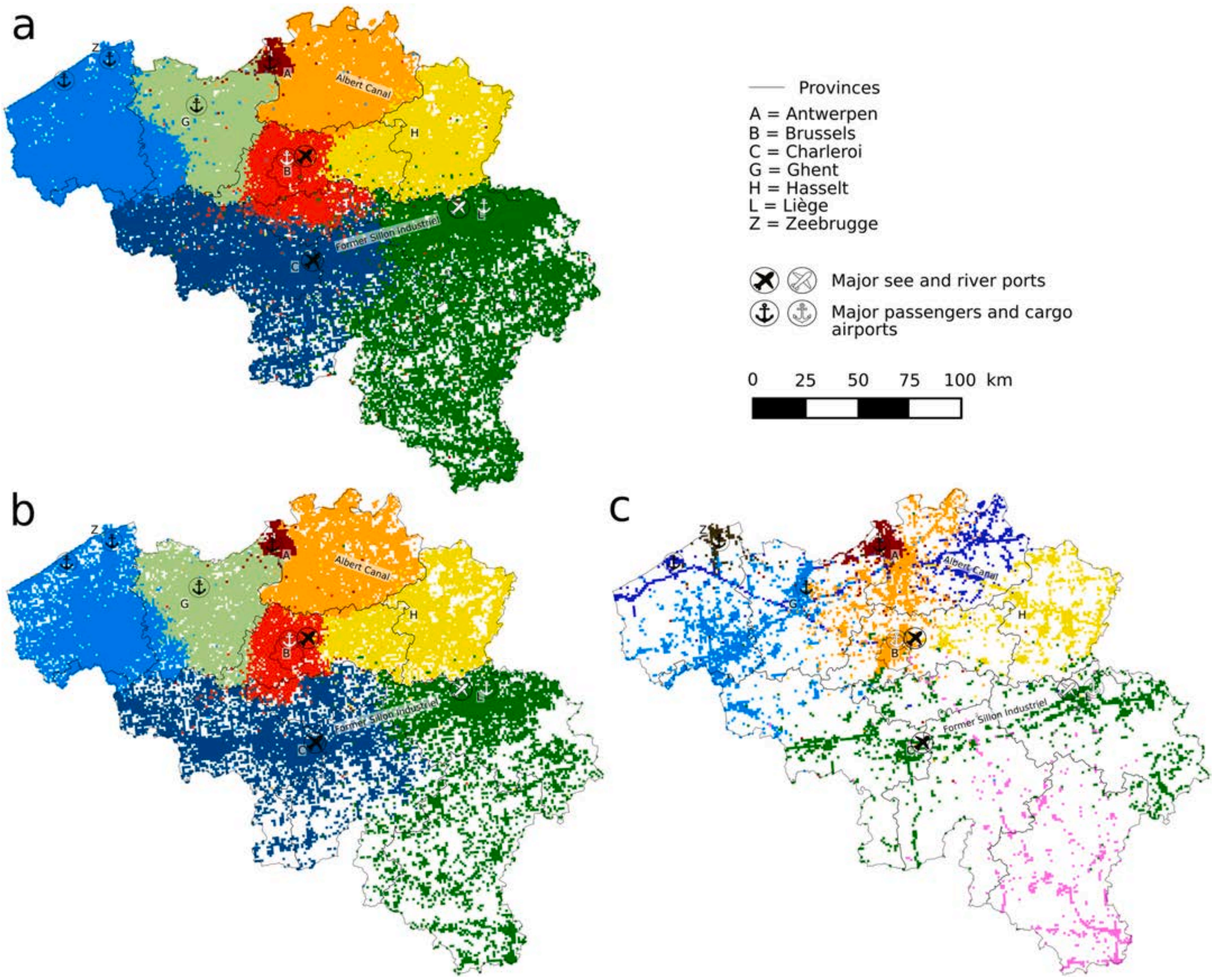

Fig. 9. Communities detected in the: a) "unpruned" general network, b) "pruned" Belgian network, and, c) "pruned" foreign network.

relevant boundaries of Brussels, as the morphological and functional extents of Brussels sprawl widely out in the Flemish and Walloon Regions (Adam et al., 2017; Poelmans and Van Rompaey, 2009; Riguelle et al., 2007; Thomas et al., 2012). In addition, provincial boundaries are also well followed, due to the provincial organization of many transportation actors (Thomas et al., 2017) and the area of influence of the secondary central places (as shown in Fig. 8a).

Nevertheless, spatial organization is not similar to the division mapped in Fig. 9c: instead of a regional polarization centered on economic poles (hubs) and cities, the structure of the road network is dominant (see Fig. 6a). Stops made by foreign trucks are mainly organized around the major transportation axes. Places visited by this category of trucks have to be easily and quickly reachable from neighboring countries. Communities have shown that some trucks are only drive through Belgium without making any stops (Fig. 8b), or within rest areas close to the main roads. For instance, the green community indicates that places located close to the German and the French borders (at two opposite sides of Belgium) have high interactions. The same effect is observed with the dark blue community found close to the border of France and that of the Netherlands. These places correspond to entry and departure areas of trucks that are only passing through Belgium, but also include several economic and logistic hubs. The general organization of the computed communities is hence an aggregate of several dimensions.

5. Discussion and conclusion

Belgian transport geography analyses have always had to deal with a lack of spatially detailed OD matrices, although they are still the most appropriate tool to analyze the structures and dynamics of territories. However, since 2016, Belgium has developed a tax kilometer system for all heavy goods vehicles with a gross combined weight of more than 3.5 tons. A GNSS mobile unit is installed in all trucks to collect their location every 30 s, and the data collected can now advantageously be diverted from their initial role to transport geography issues.

This contribution presents a framework to pre-process and clean the data that can be generalized to other Belgian transportation topics. It permits the identification of how the circulation of trucks shapes and is shaped by the geographical properties of Belgium. On the one hand, the characteristics of Belgian locations are revealed through two approaches: traffic and connections. They show distinct spatial realities (places where trucks pass, and places where they stop), but with a complementary message. One cannot exist without the other. On the other hand, a community detection method is applied to the network of origins and destinations of the trucks, hence revealing places that are closely interrelated. Communities detected in the movements made by trucks registered in Belgium are formed of contiguous places, confirming the effect of the importance of spatial proximity (Tobler, 1970, first law of geography), and the strong regional organization of the Belgian logistics sector. In contrast, stops made by foreign trucks are mainly concentrated in the easily accessible economic clusters of Belgium. Future research should be dedicated to accurately determine how strong the differences are between nationality of registration, leading to better grasp the position of Belgium in the European logistic network.

It is important to make clear that splitting all the GPS traces of trucks into sequences of segments revealing stops cannot be linked with loading or unloading activity, given that no information is available in the database, either in quantity or in nature. Moreover, the definition of the stops based on a simple arbitrary time threshold of 10 min is also questionable, although sensitivity analyses were conducted to validate this choice. Given that each truck is different (in size, nature of the delivery, working period, etc.), it is reasonable to think that stops are specific to each truck, and should be computed individually instead of using a unique threshold for the entire set of trucks in the database. The use of spatio-temporal criteria considering the function of the places visited would have allowed us to exclude some stops (e.g. for rest, comfort) based on the idea that they do not constitute a real logistic interconnection with the place visited. Future research should be dedicated to detecting these stops at the individual scale, thanks to the potentialities of machine learning techniques (Self-organizing maps or neural networks are two possible candidates). In the current era of sustainability and smart mobility, a dataset of all GNSS locations of trucks circulating in Belgium shows promising outcomes. However, one has to keep in mind that and like any sampling techniques, ICT data suffer of a lack of exhaustiveness and representativeness, as well as the absence of a validation process, that could lead to major issues. Taken with caution, Belgium has at its disposal a priceless system to measure and understand the effect of the kilometer charge system on the circulation of trucks. This could lead to new variants of taxation that should encompass all three environmental, economic and social dimensions of sustainable development.

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Appendix A

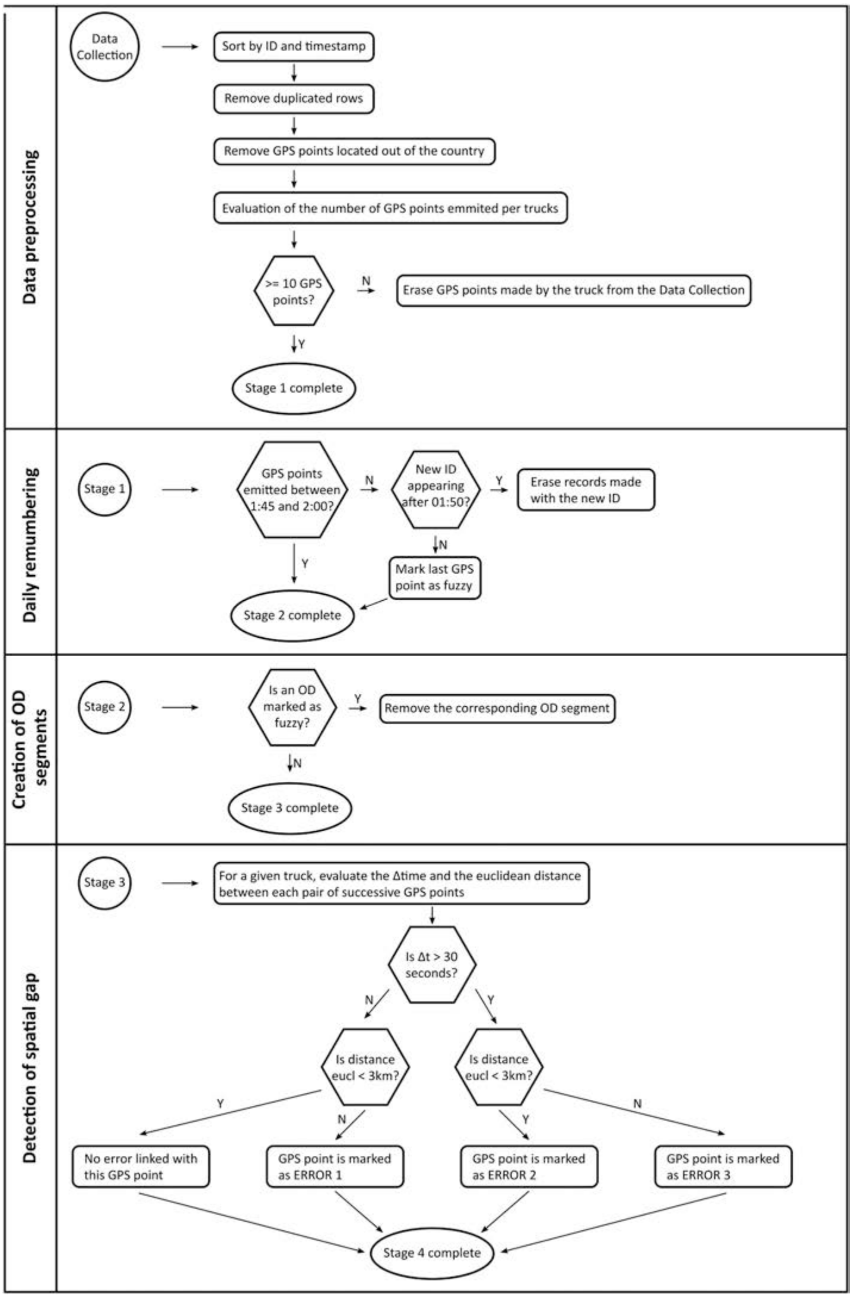

Fig. A1. Block diagram summarizing the preparation and cleaning steps.

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